



Motivation

- Climate models exhibit significant biases in their rainfall simulation (Fig. 1)
- parameterizations that are convection Moist physically motivated have failed to fully address this problem
- Why not try a purely data-driven, i.e., statistical or machine-learning (ML) approach?



Figure 1. IPCC AR5 estimate of multi model mean precipitation and bias

Approach

- Use available data to construct a predictive model of rainfall using different statistical/ML approaches
 - GPM satellite radar rainfall data
 - MERRA 2 reanalysis for atmospheric state
 - Interpolate all data to 0.5°, 3-hourly grid
- **Divide rain into 3 types** Ο
 - Stratiform (STR)
 - Deep convective (DC)
 - Shallow convective (SC)
- Initial focus on East Pacific (EP) and West Pacific (WP) regions (Fig. 2)
 - Use one year of data (2017) to train model
 - Another year of data (2018) to validate model



Figure 2. Satellite-measured annual average rainfall



Validating Rainfall Parameterizations in Climate Models using Predictive Empirical Analysis

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Figure 3. An example of a feedforward neural network

	Deep convective			Stratiform			Shallow convective		
	GLM	RF	NN	GLM	\mathbf{RF}	NN	GLM	\mathbf{RF}	NN
True Negative	0.485	0.568	0.550	0.474	0.529	0.512	0.325	0.415	0.361
False Negative	0.036	0.054	0.063	0.052	0.069	0.080	0.084	0.137	0.124
True Positive	0.122	0.103	0.095	0.188	0.171	0.160	0.267	0.214	0.226
False Positive	0.357	0.275	0.292	0.286	0.231	0.248	0.324	0.234	0.289
Total	1	1	1	1	1	1	1	1	1

Table 1. Prediction (classification) performance for each rain type (WP region)



Figure 4. GPM observed and model predicted rain rate distributions: probability density vs. rain amount (WP region)

Models

- **Random Forest (RF)**
 - Based on decision trees
- **Neural Network (NN)**
 - (Figure 3)

Conclusions

- block rain types (Table 1).
- performing much better than CAM
- easy as GLM to interpret the results.

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References



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Generalized linear model (GLM)

Logistic regression for rain occurrence

Gamma regression for rain rate

• 5-layer feed forward deep neural network

Community Atmospheric Model (CAM)

• All three methods performed well in predicting the occurrence of each of the three tropical building

• Due to the high complexity of the model structure, NN shows its advantage in characterizing the rain rate probability distributions well, even with the highly varying range of rain rates (Figure 4),

• However, high complexity raises the overfitting issue and can lead to "wrong" predictions. Compared to GLM, NN and RF are more flexible in modeling the response through a complicated function of all the predictors. But they are not as

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